TRES: MULTIRADAR-MULTISENSOR DATA PROCESSING ASSESSMENT USING OPPORTUNITY TARGETS

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ABSTRACT

In this paper we describe a new tool being currently developed by Eurocontrol for Air Traffic Control multiradar-multisensor data processing systems assessment. This tool, called TRES (Trajectory Reconstruction and Evaluation Suite), will become in a near future a replacement for some parts of current versions of SASS-C (Surveillance Analysis Support System for Centres) suite. The paper describes the overall architecture of the assessment system, and details the methods used in TRES for the calculation of reference trajectories, taking into account sensor detection characteristics, available information, sensor accuracies, biases, ... The whole system has been tested with real traffic and simulated data, some illustrative examples are presented at the end.

1. INTRODUCTION

In this paper we are describing a new tool for the assessment of multiradar-multisensor data fusion systems. The assessment of those systems is a complex problem which is usually accomplished by simulation of synthetic scenarios, or inspection of real traffic tracks. We will describe a method for the assessment of real traffic tracks based on the creation of reference trajectories by smoothing measurements from all the available data sources (primary and secondary radars, ADS, WAM). Those reference trajectories are the basis for automatic evaluation of both monosensor measures or tracks, an of multiradar-multisensor real time data processing. The comparison and performance evaluation procedure is described in Figure 1.

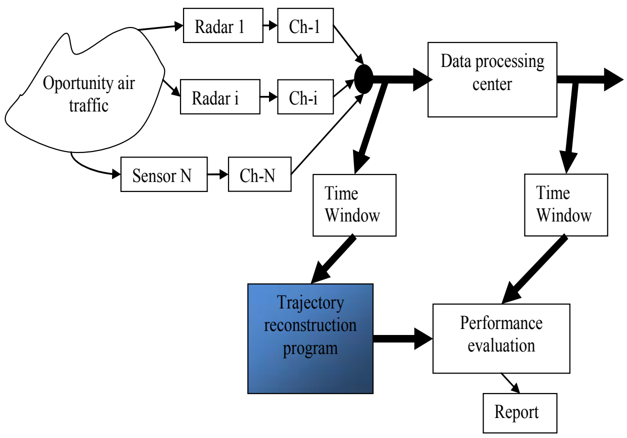

Figure 1: Trajectory assessment based on opportunity traffic

In its current state, SASS-C is a Radar Plot Evaluation and Radar Tracker Analysis tool [1]. It is usable to assess both monoradar and multiradar deployments during system commissioning, installation, operational life, and during incident investigation. The system contains means for:

- recording radar data,
- performing multiradar chaining (association) using a module called Object Correlator,
- performing radar bias estimation [2] and trajectory interpolation using the Muratrec interpolation system.
- inserting simulated data, by means of the companion SMART system.
- graphical display of measurements.
- coverage prediction and evaluation.

As new sensors appear in ATM (ADS, WAM, 3D primary radars), Eurocontrol faces the problem to keep updating current monolithic SASS-C versions with new modules (suites) and functionalities, or replacing it with a new design. This new design, from the beginning, takes into ac-

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count the different roles the software must play, and therefore it is integrated by several cooperating programs:

- Recording radar data is performed by MAS (Multi-source Acquisition Suite) system. This is a pre-existing ATC data recording product from COMSOFT, which has been adapted to be part of the new SASS-C. This suite has also the capability of replaying radar data inside SASS-C data-base and injecting them in a real tracker.
- Association, bias estimation and correction, and trajectory interpolation are performed by the new OTR (Opportunity trajectory Reconstruction) module. This module must not only use radar data, but it has been designed taking into account the current and near future sensors in ATC surveillance. Even more, the architecture has been developed in a way in which integrating new measures is relatively straightforward. The main product of this module is the list of reconstructed trajectories from all targets in the interest area.
- Assessments over plots and tracking statistics are performed by CMP (Comparator) module. It uses reconstructed trajectories from opportunity traffic (provided by OTR) and analyses radar and tracking behavior (probabilities of detection, false alarms, accuracy, …)
- In order to further investigate anomalous results, a software tool-set (CAI: computer aided investigation) has been developed to help user in the analysis of OTR and CMP results. The graphical display of results is performed, in current design of the system, by reusing MAS display capabilities.
- SMART system may be used to feed SASS-C analysis with simulated data. This data can be injected in a real tracker using the "replay" functionality of MAS.
- SCAS can be used to generate coverage maps and this information used by CMP and CAI for tracker and sensor performance analysis.

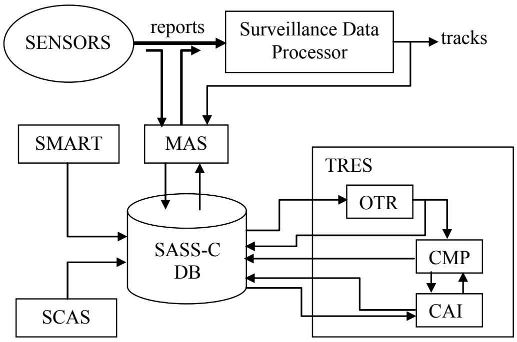

Figure 2: SASS-C new architecture

All applications now share a common database (the SCDB, or SASS-C data base). So, each module is potentially interchangeable with another module provided inputs and outputs are respected.

OTR, CMP, and CAI form what, in new SASS-C, is known as TRES. This paper is centered in the description of TRES. Figure 2 shows the overall SASS-C architecture.

2. TRES TECHNICAL DESCRIPTION

TRES is in itself a suite composed of three elements (OTR, CMP and CAI), working over data injected in SCDB, and fulfilling the following general requirements:

- Its first version must work with the following sensors:
    - Secondary radars, both conventional and Mode S.
    - Primary radars, providing either 2D (range, azimuth) or 3D (range, azimuth, elevation) measures.
    - Wide Area Multilateration (WAM) systems, obtaining measures from either Mode S or SSR squitters or replies to radar interrogation.
    - ADS-B, with several potentially coexisting stations, which may have different communication technologies.
- Those sensors obtain their measurements using different procedures. Data are provided in different coordinates, with different systematic and stochastic errors… The different measures obtained from all sensors will be called target-reports in the following paragraphs.
- Data fusion to be performed in OTR demands time and space alignment of different sensors systematic errors. The error components to be taken into account are:
    - For all radars: Range bias, Range Gain, Azimuth bias, Azimuth eccentricity, and time offset between sensors.
    - Additionally, for secondary radars, response delay offset, different for each transponder.
    - For ADS-B, time and position offset, different for each aircraft.
    - For WAM system, a map/grid with position offsets depending on the position.
- Target-report association to reconstructed trajectory must take into account the different data (and its integrity) provided by the sensors: Mode A, Mode S, position, barometric (derived from Mode C) or geometric (from primary radar elevation, aircraft navigation system in ADS-B, or multilateration based) height. Depending on the sensor, the available data is different, and therefore the association procedures must be different.

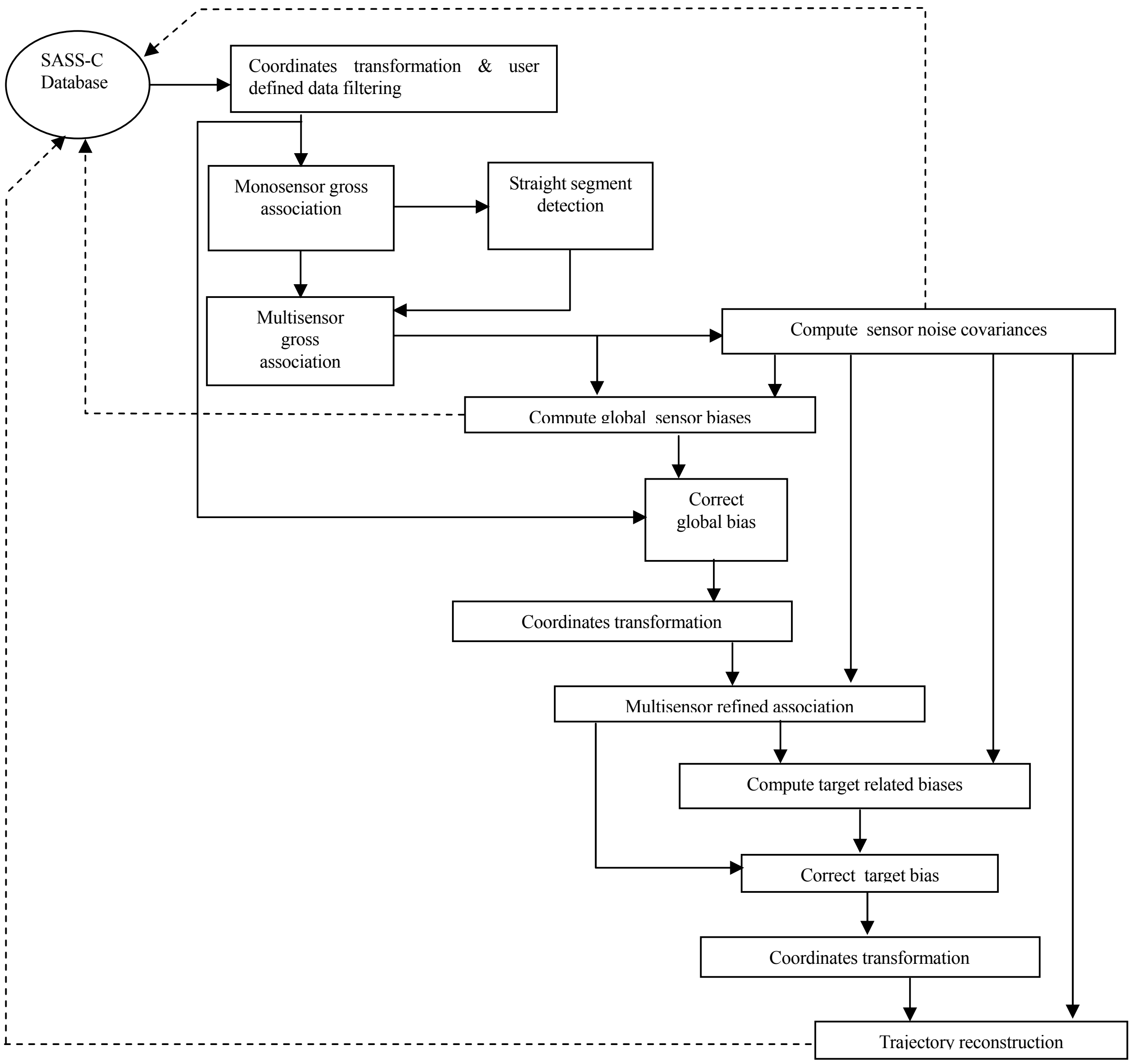

Figure 3. OTR Architecture

- It is an offline system. Therefore, association need not be performed as a first stage, but, for not so clear cases, it may be delayed until more information is available. For instance, reconsiderations over associations are defined after systematic error correction.
- New sensors allow the potential inclusion of geometric height in the ATM procedures and ATC systems. While more operational confidence is gained over this data, OTR includes means to gain advantage of this information, while not perturbing potential assessments of barometric height measurements or barometrical height tracking.
- TRES takes advantage of geographical information, in the form of coverage, screening files, airport databases, …
- It allows for data filtering at several stages, using either database methods, or built in filters (geographical, by sensor, by any code, by type of traffic, …).

Its main purpose is the assessment, using real traffic, of both sensor characteristics and of real time tracking systems.

3. OTR TECHNICAL DESCRIPTION

The design of Opportunity Trajectory Reconstruction (OTR) algorithms has the philosophy of reducing interaction with TRES user. The objective is that user should not specify

OTR parameters related with smoothing data and sensor bias estimation. OTR works as an special multisensor fusion system, aiming to estimate target kinematic state, in which we take advantage of knowledge of future target position reports (smoothing). Figure 3 presents the block diagram of OTR algorithms. We will detail its steps in the following subsections.

ASSOCIATION, NOISE CALIBRATION AND BIAS ESTIMATION AND CORRECTION

The first task in trajectory reconstruction is to put all measurements in the same coordinates system and correct systematic errors of each sensor. The system will use stereographic projection. The measurements of each sensor are converted from its measured coordinates system to stereographic central coordinates. If information about sensor measurement noise exists, it is also converted to noise covariance matrix in central coordinates. Next we select the data for Trajectory reconstruction applying filters specified by TRES user in order to allow exclude manually data items.

The following step is to group sensor data in mono-sensor tracks related with a target, and monosensor tracks among them to form multisensor tracks. This is a prerequisite for all functions. To do that, association algorithms takes into account code information, position compatibility, time of measurement compatibility, velocity on segments compatibility, etc. In this first stage, the association method should be conservative to permit a confident bias estimation, because a later stage will refine the association.

There could be problems in the noise parameters injected by the user, and so overall system robustness and precision will be enhanced with the estimation of sensor noise covariance.

The user could fix certain biases as correct and let the OTR algorithm determine the rest of the parameters. For each track we determine segments of rectilinear uniform mode of flight (MOF). The data in these segments will be used to estimate non corrected sensor biases. The data in rectilinear segments is used for bias estimation avoiding problems with the systematic errors in position predictions associated to target manoeuvres. These data are injected into the bias estimation algorithms. They are based in the Kalman filtering of error model parameters for each sensor. Models appropriate for each sensor have been derived. Data for the same track segment are used to estimate sensor biases for all the sensors feeding the track in the segment. Then, the track related estimates are combined and sensor global biases are derived. Finally, the system corrects biases and group data.

As bias models include bias terms related with all traffic and others related with each individual target, the bias estimation/correction must be performed in two steps:

1. Global bias estimation and correction for bias terms related with all traffic.
2. Target bias estimation and correction for bias terms related with each individual target

After global bias correction, data association may be enhanced, as we can reduce spatial compatibility gates and use aligned data. A process for association refinement is then set, which allows for more aggressive association heuristics, as bias estimation will be not corrupted by any problematic association.

RECONSTRUCTION ALGORITHMS

The trajectory reconstruction uses all reports associated to the multi-sensor trajectory, expressed in common coordinates, and with systematic errors of each sensor corrected. This process is based on the segmentation phase dividing reports from the trajectory in time intervals corresponding to different Modes of Flight (MOFs). With this information, the reconstructed trajectory is interpolated in each segment using filtering models matched to the MOF segments using the parameters describing each segment. The 3D reconstruction is separated into 2D horizontal and vertical components, both for MOF recognition and for trajectory interpolation.

Figure 4 summarizes the reconstruction process. It consists in a double tracking loop in the forward and backward directions, both for MOF classification and trajectory reconstruction, with appropriate filtering techniques and dynamic models for all representative situations. These loops have the following functions:

1. Determine segments with uniform MOF.
2. Detect outliers and solve problems of association of target reports to multiple tracks.
3. Detect missed target reports.
4. Reconstruct trajectories with position, velocity and acceleration estimates.
5. Assess quality of reconstructed trajectories, characterizing error ellipses and envelopes.

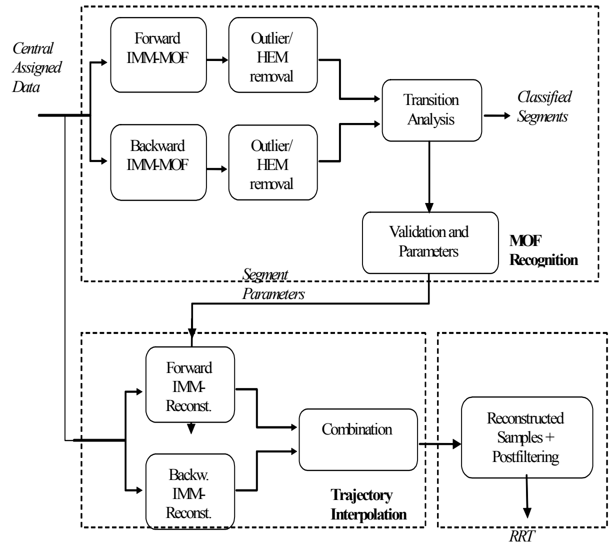

Figure 4: Block diagram of reconstruction algo-

Finally, after these loops, the reconstruction information is used for final interpolation and post-filtering issues covering the requirements on gap extrapolation, correlation of enrichment of external trajectories, analysis of missed reports and track classification.

The MOF recognition and classification phase provides an initial classification for the set of multi-sensor data contained in each trajectory. It divides segments with different modes of flight (MOF). This MOF segmentation basically defines time intervals containing multi-sensor data corresponding to different types of motion: uniform motion, turns, and longitudinal maneuvers. This process is based on a set of matched Kalman filters used to estimate the probability of target flying accordingly to the different modes defined. For this application, one of the techniques in the state of the art in tracking filter has been employed, Interacting Multiple Mode (IMM) filters, with appropriate mode matched to each considered MOF. This type of tracking filters has been extensively applied to ATC systems [3,4]. Since this kind of filters can have problems to detect ends of maneuver segments, the forward and backward filter running are complementary to address this problem effectively and take advantage of the use of past and future measurements. The execution of IMM tracking filter forward and backward over data in the trajectory allows estimation of probabilities for each mode of flight in both directions [5]. This is used to identify the start and end of typical maneuvers to build the segments dividing the trajectory (see Figure 5).

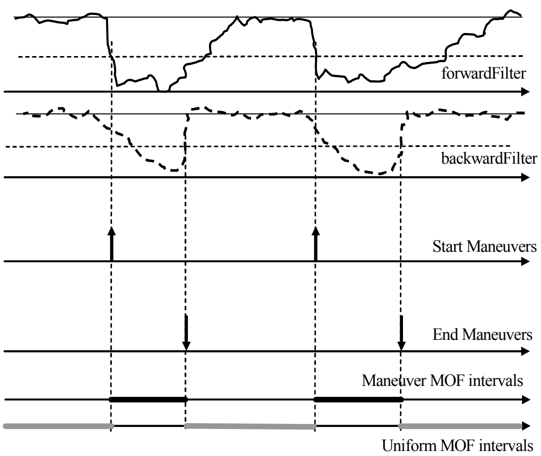

Figure 5: Illustration of MOF segmentation with forward-backward filters

The parameters describing each MOF segment are computed for validation and for estimation of the final MOF category and level of confidence. These segments are additionally used in the comparator module to compare two RTs regarding MOF. These MOF parameters are used by the final reconstruction algorithms to refine the transitions among different modes of flight and compute their parameters accordingly to the available data. The outlier removal is also done at this phase to avoid triggering bad modes of flight. This logic basically analyses the residuals (difference between observations and tracker predictions), weighted with their associated covariance matrices, in order to identify those measurements with anomalous deviations.

Also, in a separated step, all missed target reports are computed, using sensors' time scan, and considering special cases for ADS data possibly belonging to overlapped stations and data from combined primary-secondary radars. Besides, directly related with outlier removal, maneuvers of very high acceleration (High Energy Maneuvers, HEM) receive special attention. In these cases, very few reports in the MOF segment would be available to perform any reasonable interpolation, so these segments are marked to preclude interpolation applied in the rest of cases. The logic for HEM detection is an extension of outliers' logic.

After MOF reconstruction, tracking filters specialized for rectilinear segments and for non-uniform motion are applied to provide the best reconstruction of the real trajectories followed by all targets in the recording. They interpolate, using IMM forward-backward filters, the state vectors corresponding to available measurements, taking also into account the maneuvering parameters describing the "mean" values along the segment, but adapted to the specific conditions of the time segment including the target reports. This solution, an extension with respect to previous proposals also based in forward-backward runs [5,6], imposes continuity conditions in speed and position with adjacent segments, allows a high smoothing to filter out noise, and also adaptation to dynamic conditions of maneuvers (for instance, the transversal acceleration or longitudinal acceleration may change along a turn trajectory).

The quality of segment interpolation is attached here to each segment of a reconstructed trajectory. The estimation of the uncertainty will include the standard deviation of target position, both for each position with ellipse error parameters or both the trajectory segments, with the envelope of ellipse errors which can be also used to display the volume corresponding to targets with probability 95%.

This reconstruction is done first for time registers corresponding to all available reports. Afterwards, the final set of reconstruction samples are generated through interpolation with a criterion of bounded error. The minimum possible set of samples are stored, considering the distortion due to stereographic projection in uniform motion and maximum linear errors for maneuvering segments to derive a minimum time separation between samples.

Reconstruction phase ends doing a post-filtering function covering association and enrichment of external trajectories, and merging of trajectories with large gaps within, taking into account forbidden extrapolation cases (landing/take-off and coverage enter/exit pairs of trajectories).

Finally, in this block the trajectory will be classified into aircraft classes, within certain confidence levels, using information from reconstructed trajectory parameters (velocity, height, maneuvering parameters, etc.).

4. RESULTS AND CONCLUSION

The performance of proposed OTR algorithms were analysed in some simulated representative situations, with the typical magnitudes of speeds and manoeuvre accelerations and different sensor configurations. The MOF classification obtained satisfactory results (the right sequences of segments, with small errors in the time edges). Regarding the accuracy performance in position and velocity, the values obtained were consistent with the error bands corresponding to 96%, and a significant improvement was observed when DAP-ModeS or ADS-B velocity was included in the interpolation.

Also, bias estimation procedures were validated in simulated scenarios, where we obtained accurate estimate of the simulated biases, which were consistent with the simulated bias values and with their associated covariances.

With an illustrative purpose, we present here some examples of reconstructed trajectories with real data close to an airport area, where we have a set of aircraft in the take off and climb phases. We are selecting these trajectories as they are among the most problematic for commercial controlled traffic for the reconstruction due to:

- Their higher lateral manoeuvrability.
- The change of height and related change of velocity as the aircraft climbs.

In figure 6, we can appreciate the sensor data and reconstructed trajectories, in horizontal and vertical planes. The detected outliers ("OUT") and missed reports ("MISS") are also indicated, events used in the CMP module to analyze the sensors performance.

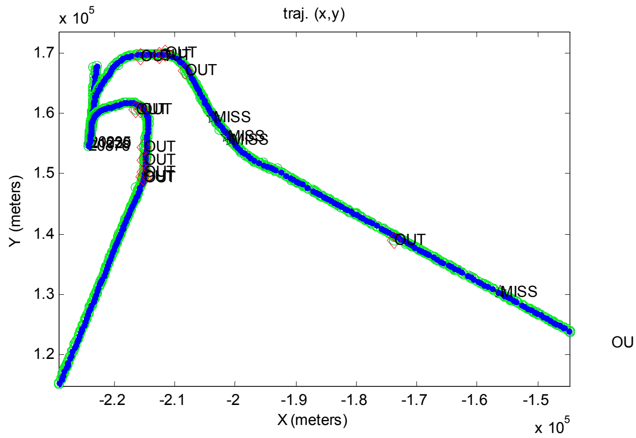

Figure 6: Reconstructed departures trajectories

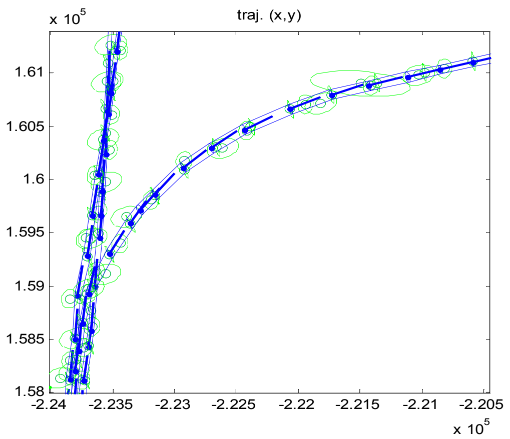

Figure 7: Horizontal reconstruction (detail)

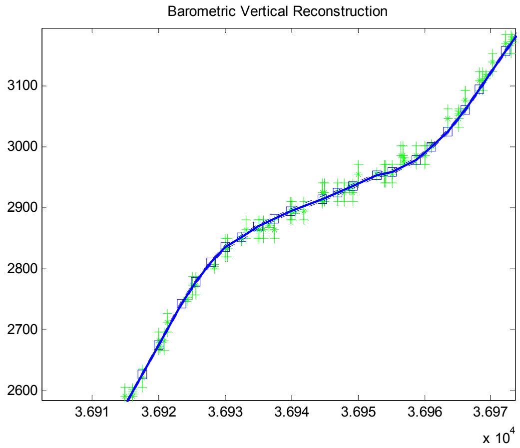

Figure 8: Vertical reconstruction (detail)

Figure 7 has the detail in horizontal plane, indicating the uncertainty ellipses of measures and reconstruction, and figure 8 presents the detail of vertical reconstruction, indicating the barometric quantization interval. As we can appreciate, heterogeneous data were correctly aligned after bias removal so that the reconstruction could build a smooth reference curve for evaluation. Regarding the segmentation of mode of flight, the results are also satisfactory, with the detection of turns and longitudinal accelerations in horizontal plane, and climbing in the vertical plane.

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